Investigation of Carbon-Reinforced Acrylonitrile Butadiene Styrene 3D-Printed Honeycomb Composites

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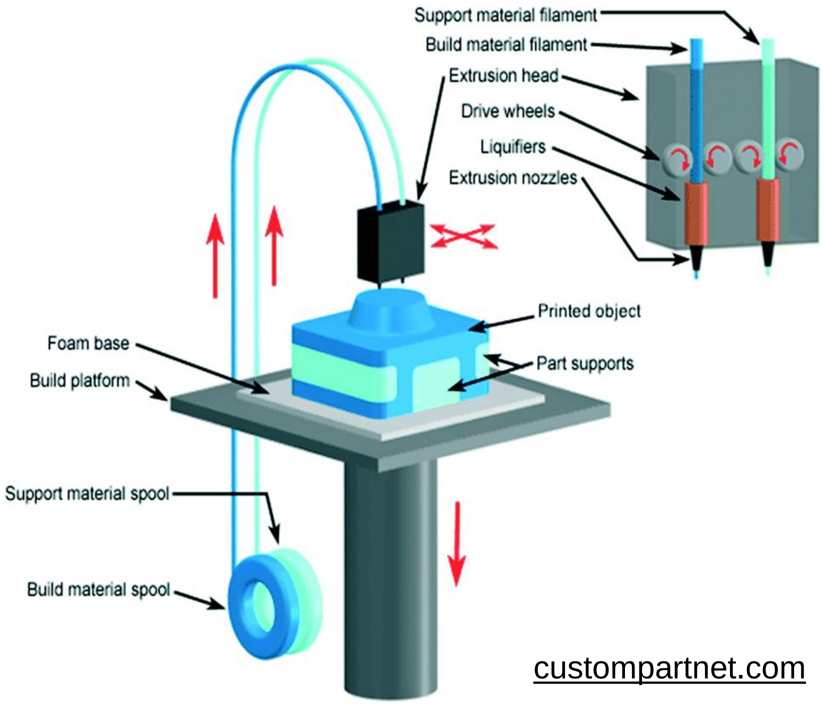
Outline

- **Introduction and Background**
  - Material Development and Design in Additive Manufacturing (AM)
- **Objective**
- **Materials and Methods**
- **Results and Discussion**
  - Experimental
    - Microscopy | Compression Testing
  - Computational
    - Classification | Regression
- **Concluding Remarks**

Material Development and Design in AM

Fused Filament Fabrication (FFF)

- Layer-by-layer manufacturing
- Multi-material components
- Thermoplastics | Metals | Ceramics



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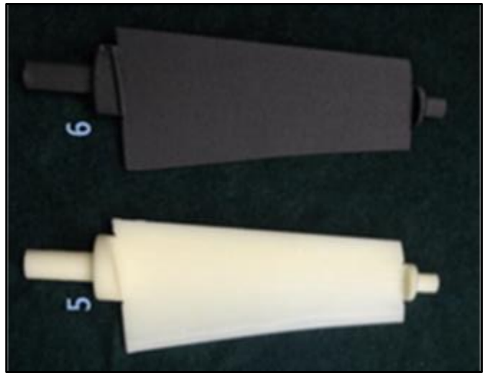
Improved Performance

- Multifunctional design
- Complex geometry
- Topology Optimization
- Reduced Weight

Manufacturing

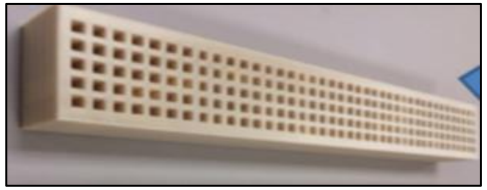
- Less Waste
- Shorter lead time
- Prototyping

Battery Thermal Management Pack



Engine Inlet Guide Vanes

Engine Panel Access Door

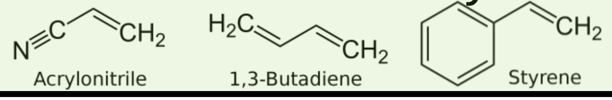


Acoustic Liner

Material Development and Design in AM

Impact resistance
Heat resistance
Electrical resistance

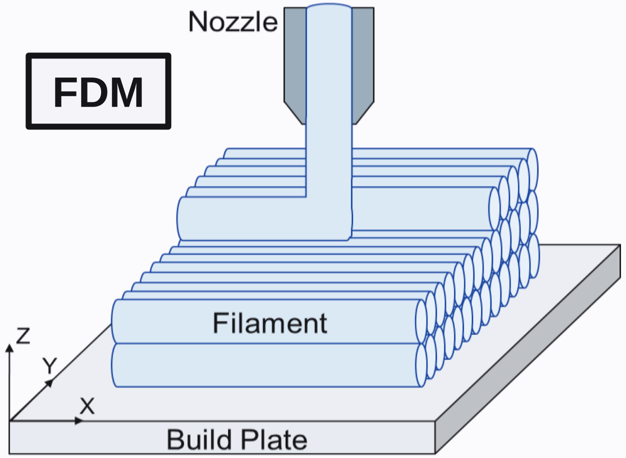
Acrylonitrile Butadiene Styrene (ABS)



Recyclable
Prone to warping

Process

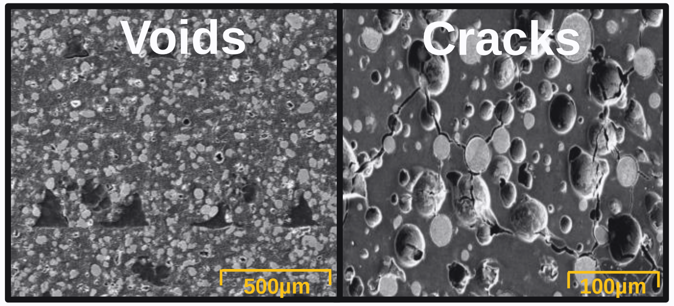
FDM

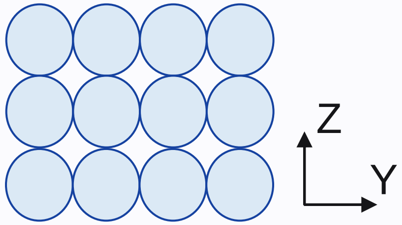


Parameters

Print speed
Raster pattern
Layer thickness
Nozzle size/temperature
Build plate temperature
Feedstock properties

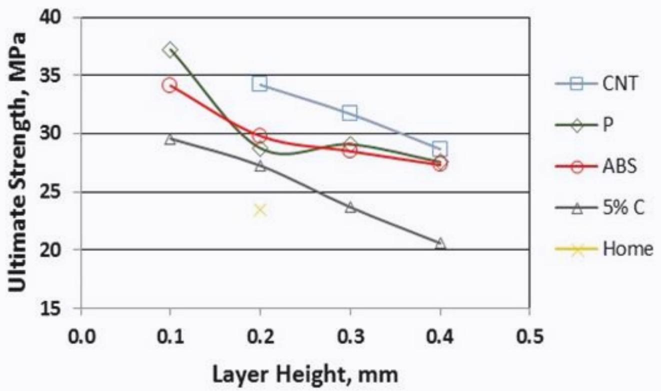
Structure





Anisotropy

Property



Filaments used: ABS-standard abs, P-premium abs, CNT-w/carbon nanotubes, C-w/chopped carbon, Home-lab extruded filament

Functional

Wear Resistance
Vibration Dampening
Thermal Management
Acoustic Attenuation

Performance

Honeycomb Structure

Variable Geometry

Panels for acoustic treatment

Objective

Determine the effect of 3D printing parameters and carbon-reinforcement on acrylonitrile butadiene styrene (ABS) polymer composites for novel high-performance and lightweight 3D printed structures.

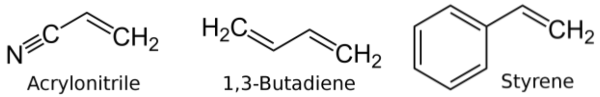
1. Leverage microscopy techniques and mechanical testing to investigate and evaluate processing-structure-property (PSP) relationships.

2. Leverage machine learning to construct models based on PSP relationships to classify materials and predict material properties.

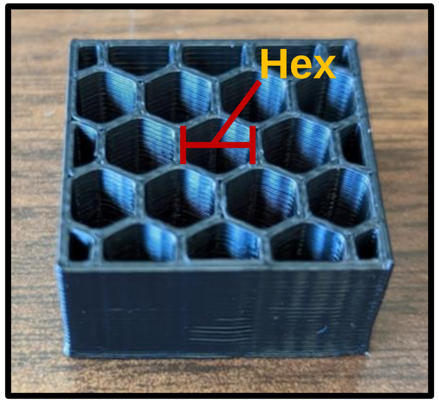
Materials and Methods

Materials

Acrylonitrile Butadiene Styrene



- Plain ABS (ABS) [3DXTech]
- Carbon Nanotube - Reinforced ABS (CNT) [3DXTech]
- 5wt.% Chopped Carbon Fiber - Reinforced ABS (CF) [3DXTech]



Features

- Hex Sizes: [5.46 | 5.72 | 5.97 | 6.22 | 6.48 | 6.73 | 6.99] mm
- Layer Height: [0.2 | 0.3] mm

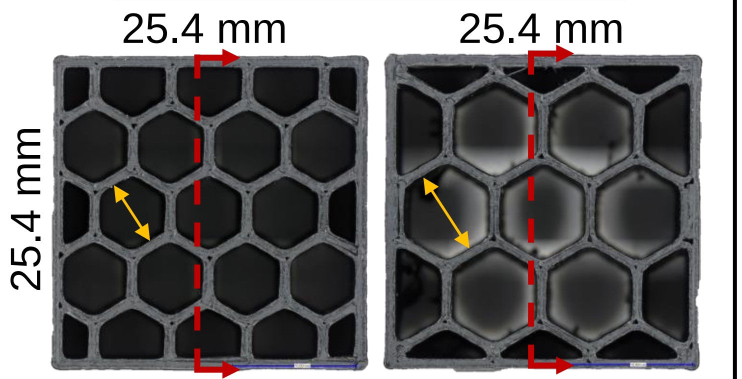
Methods

1. Optical microscopy of as-fabricated samples
2. Compression testing of ABS and carbon-reinforced polymer composites [ASTM D695-15]
3. Machine learning for classification and regression of material and properties

Characterization and Testing of Additively Manufactured Carbon-Reinforced ABS Composites

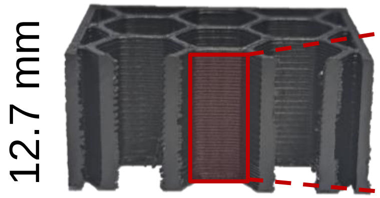
Optical Microscopy of Materials

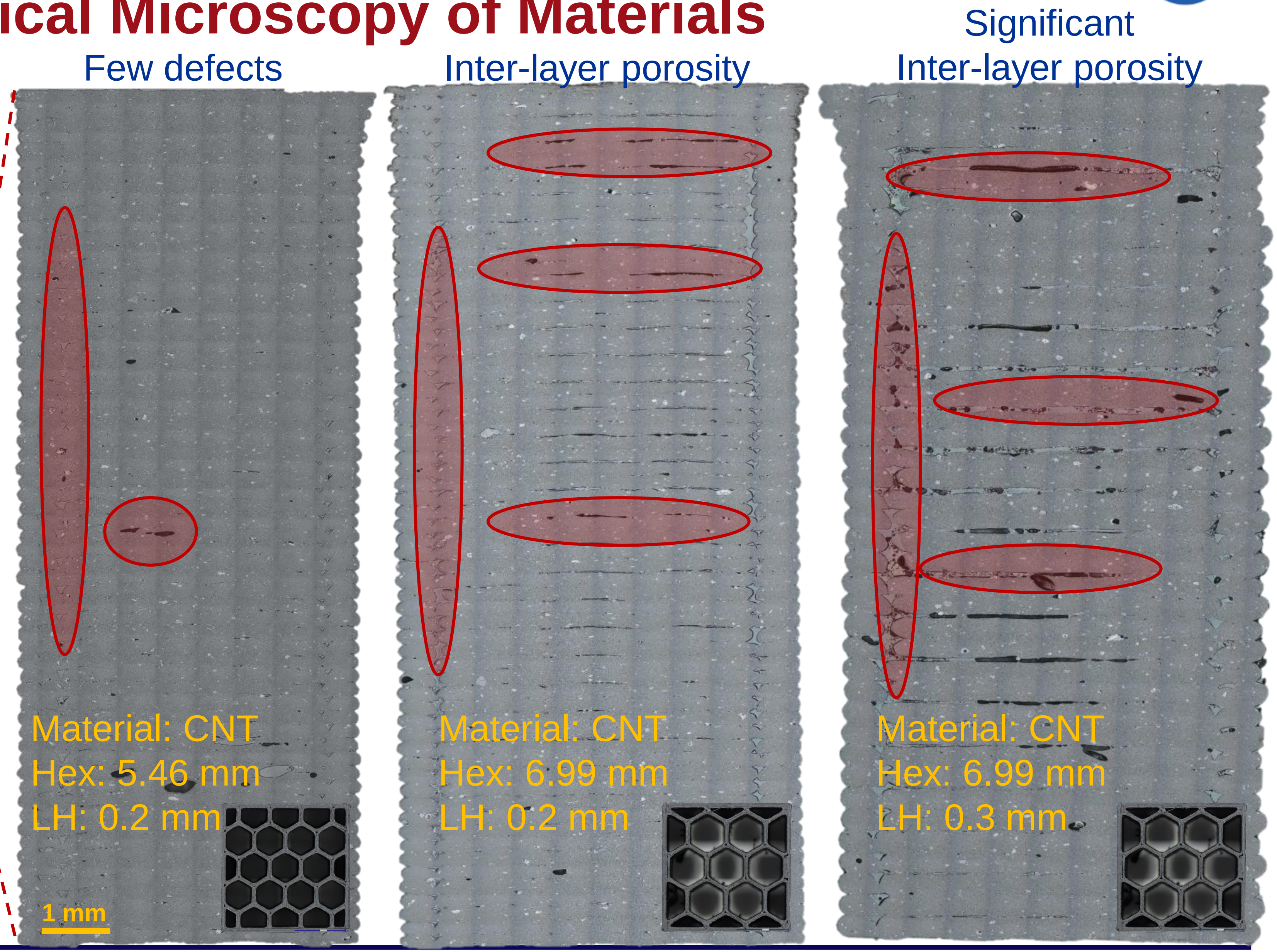
Honeycomb Hex Sizes



Hex: 5.46 mm Hex: 6.99 mm

Layer-wise Cross Section



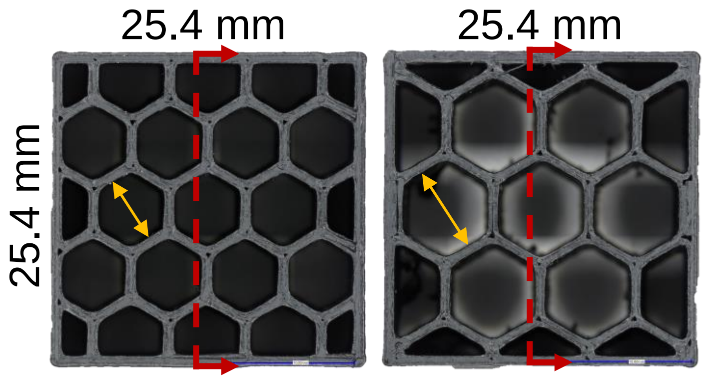


Observations

- Increased porosity with increasing hex size and print layer height
- Significant porosity along honeycomb vertices

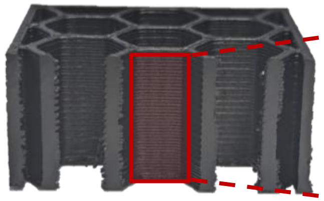
Optical Microscopy of Materials

Honeycomb Hex Sizes

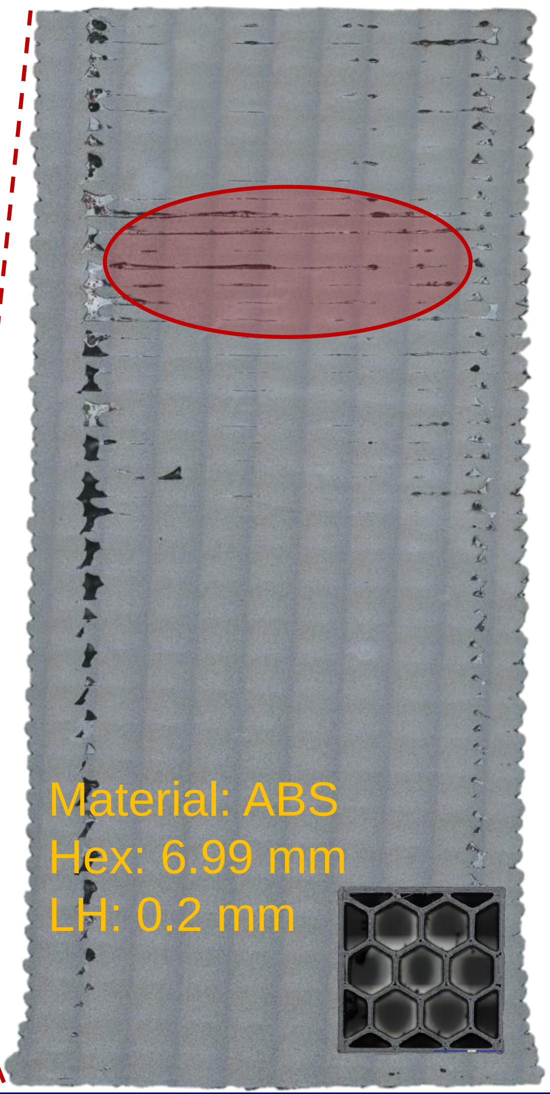


Hex: 5.46 mm   Hex: 6.99 mm

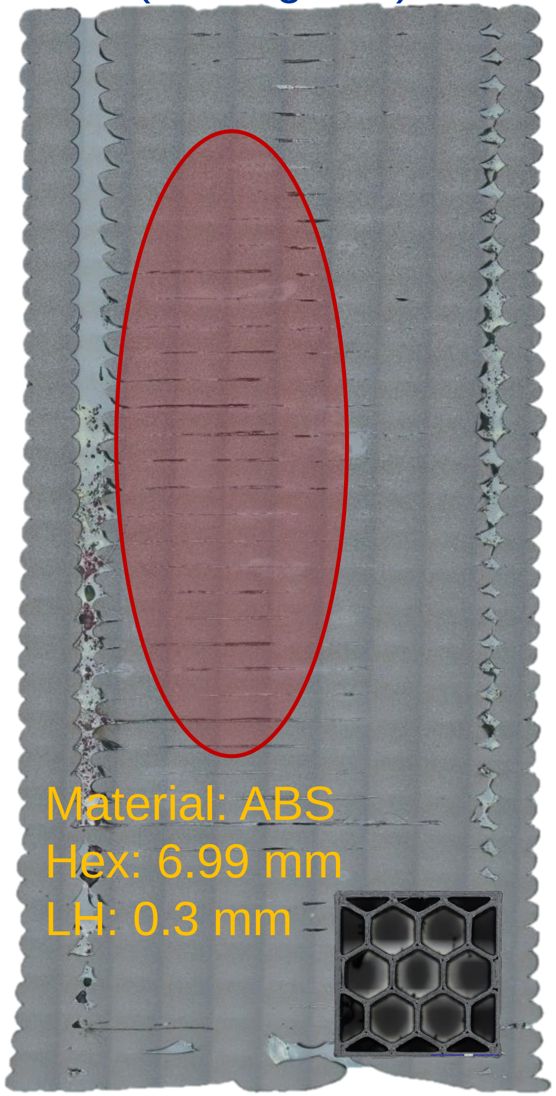
Layer-wise Cross-Section



Inter-layer porosity (Partial)



Inter-layer porosity (Throughout)



Observations

- Increased porosity with increasing layer-height
- Less inter-layer porosity than carbon-reinforced counterparts
- Inherent porosity along honeycomb vertices

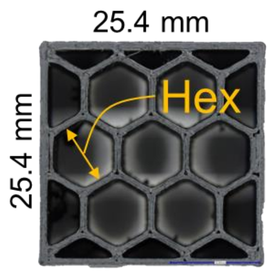
Compression Testing

Experimental Details

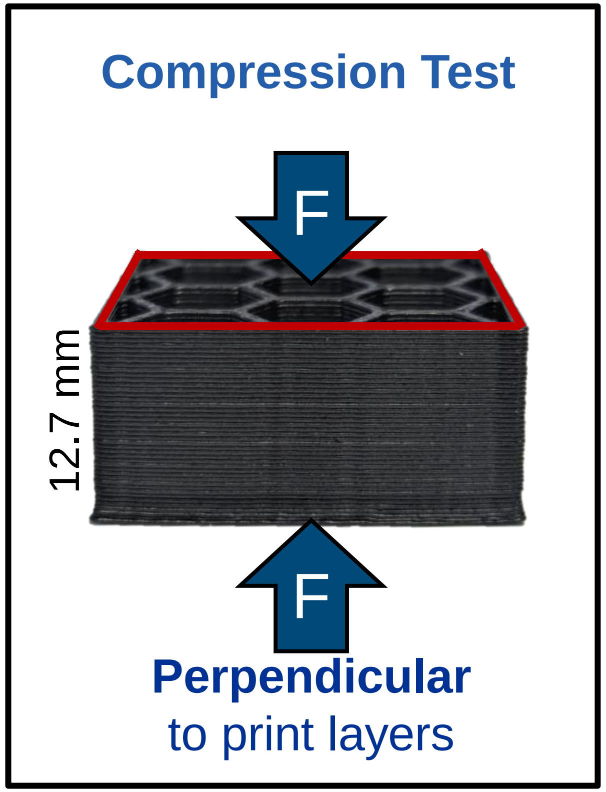
- ASTM C365
  - Flatwise Compressive Properties of Sandwich Cores
  - Dimensions (Length x Width x Height): [25.4 x 25.4 x 12.7] mm
  - Load speed: 6 mm/min
- Total number of samples: 65

Features	Properties
Material	ABS | 5 wt.% CF-ABS | CNT-ABS
Hex Size [mm]	5.46 | 5.72 | 5.97 | 6.22 | 6.48 | 6.73 | 6.99
Layer Height [mm]	0.2 | 0.3

- Perpendicular to print direction
- Digital Image Correlation

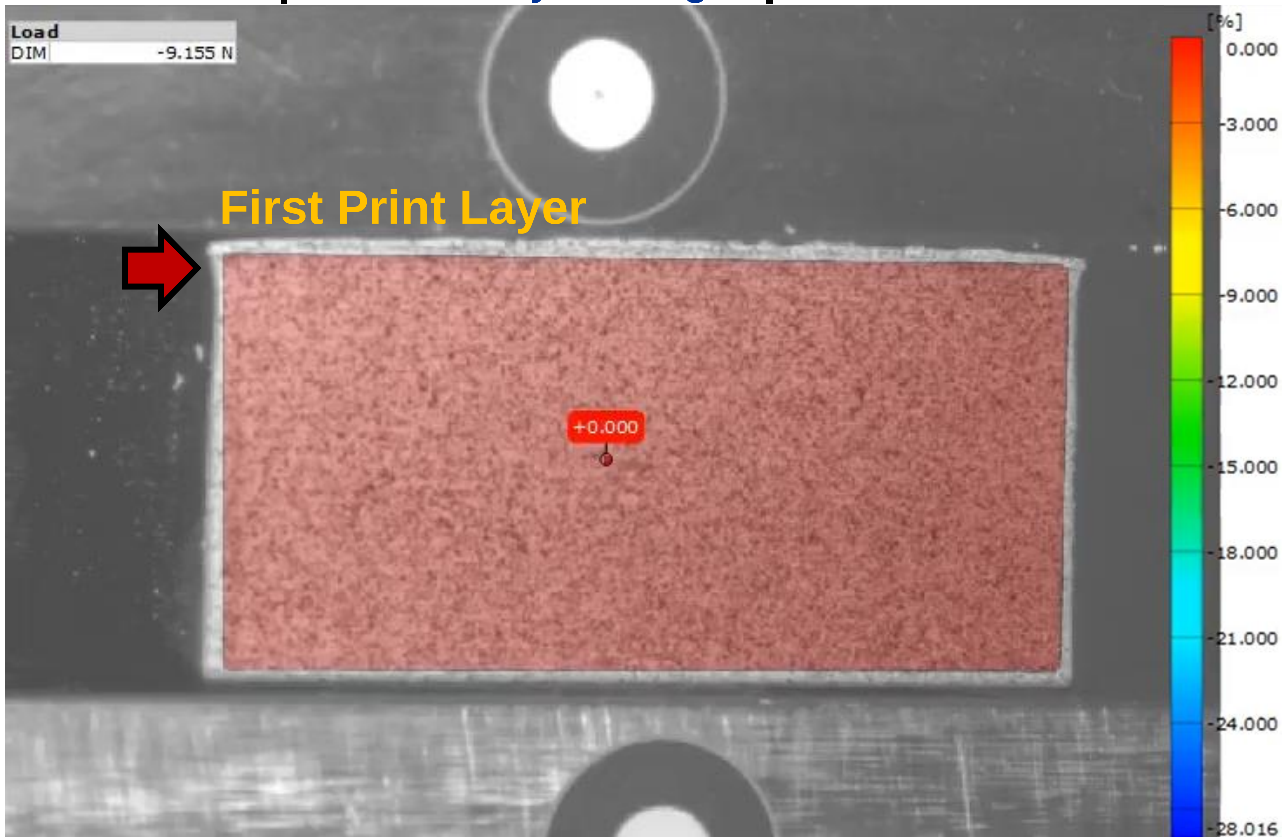


Cross-Sectional Area

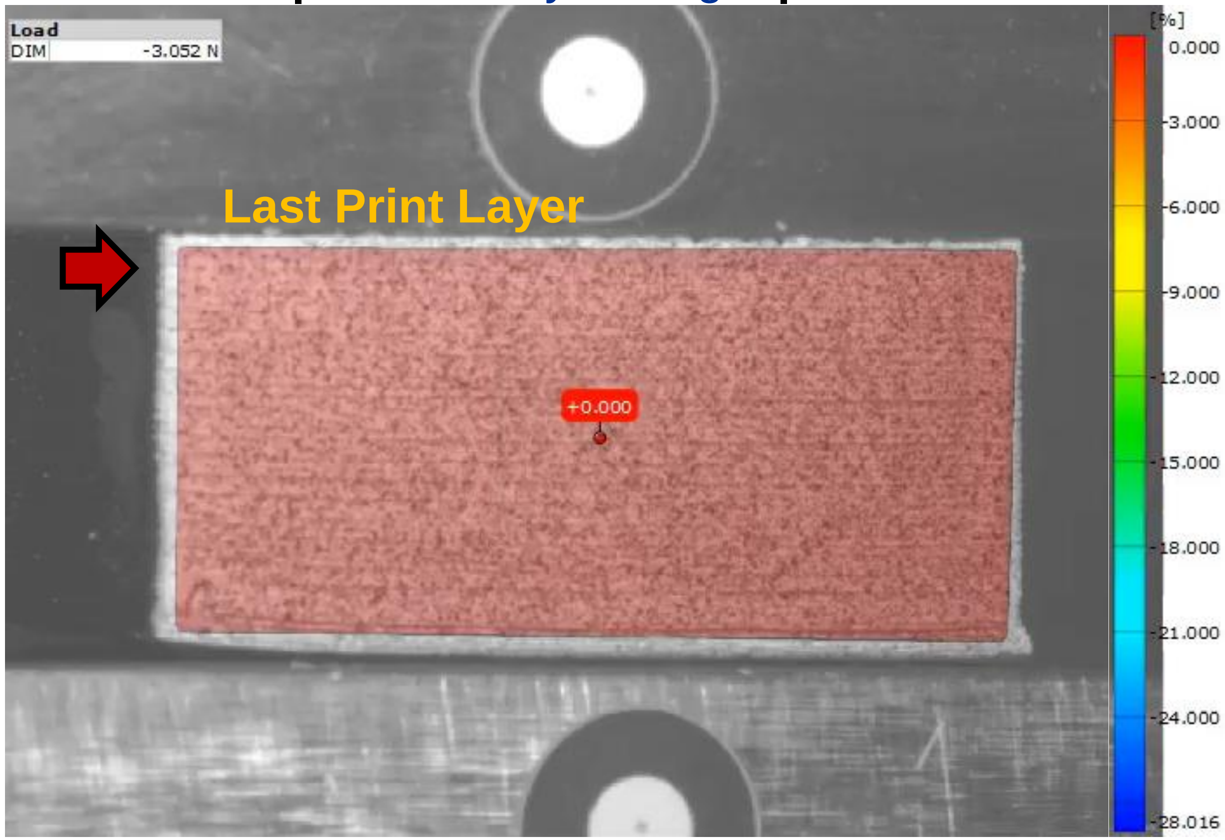


Compression Testing – DIC

ABS | 0.2 mm Layer Height | 5.46 mm Hex



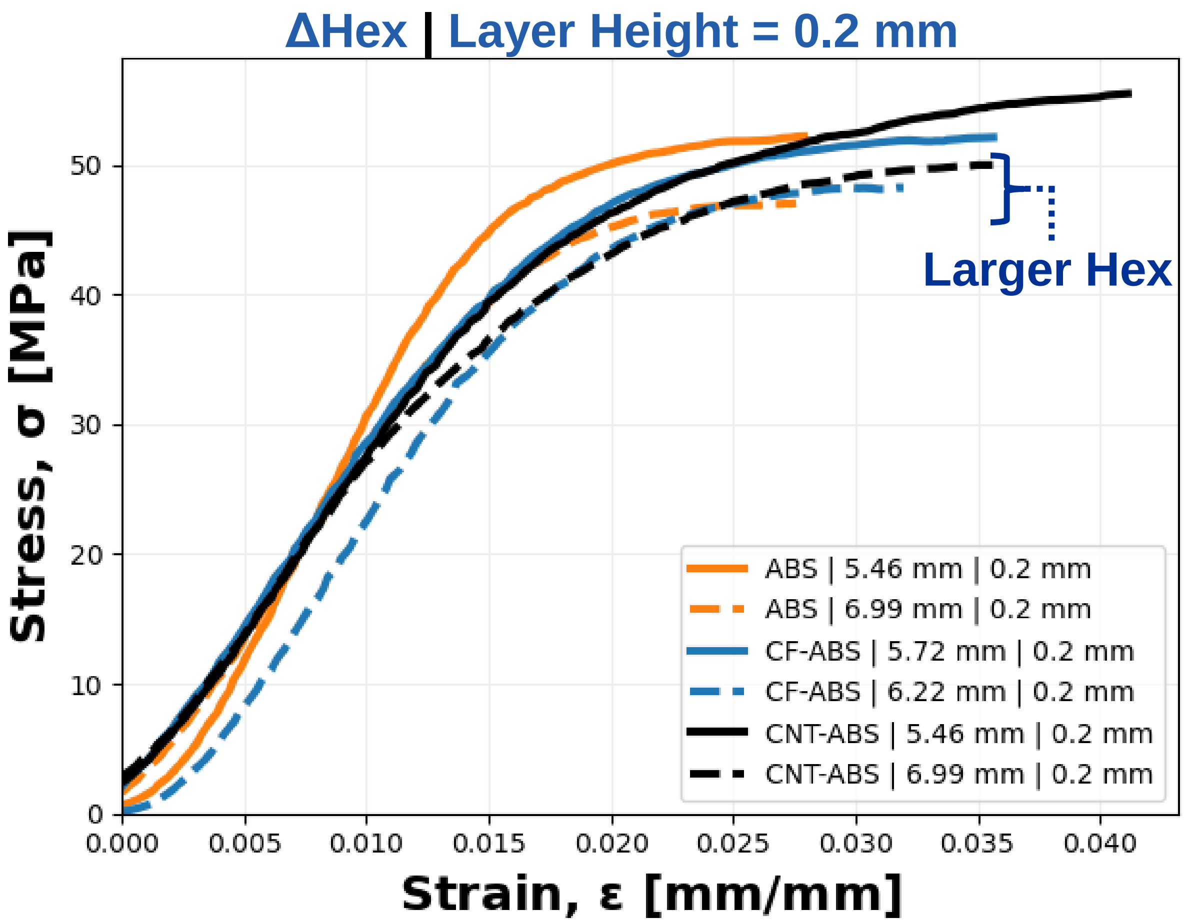
CNT-ABS | 0.3 mm Layer Height | 6.99 mm Hex

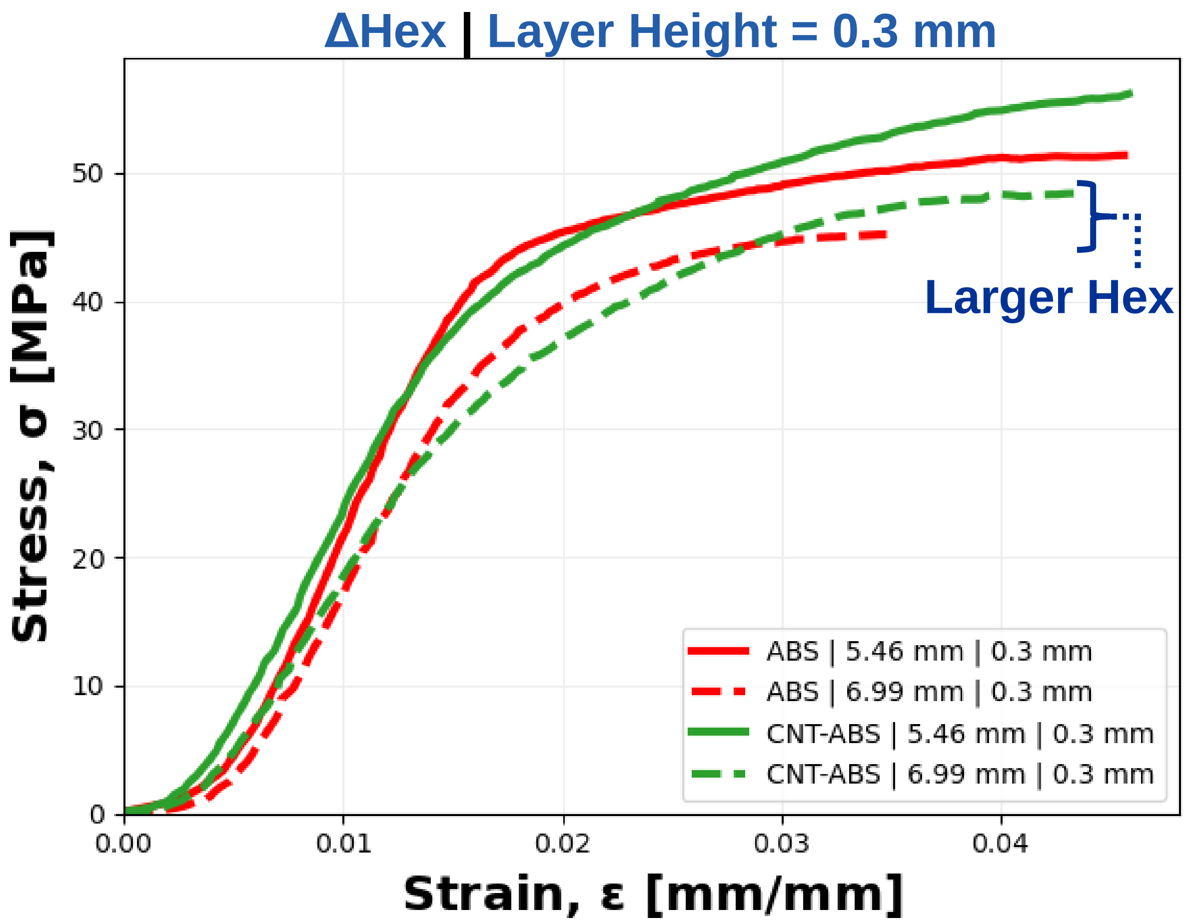


Coupons failed by inter-layer rupture towards upper half of print, regardless of test orientation.

- Possibly a result of increased porosity in upper print layers.

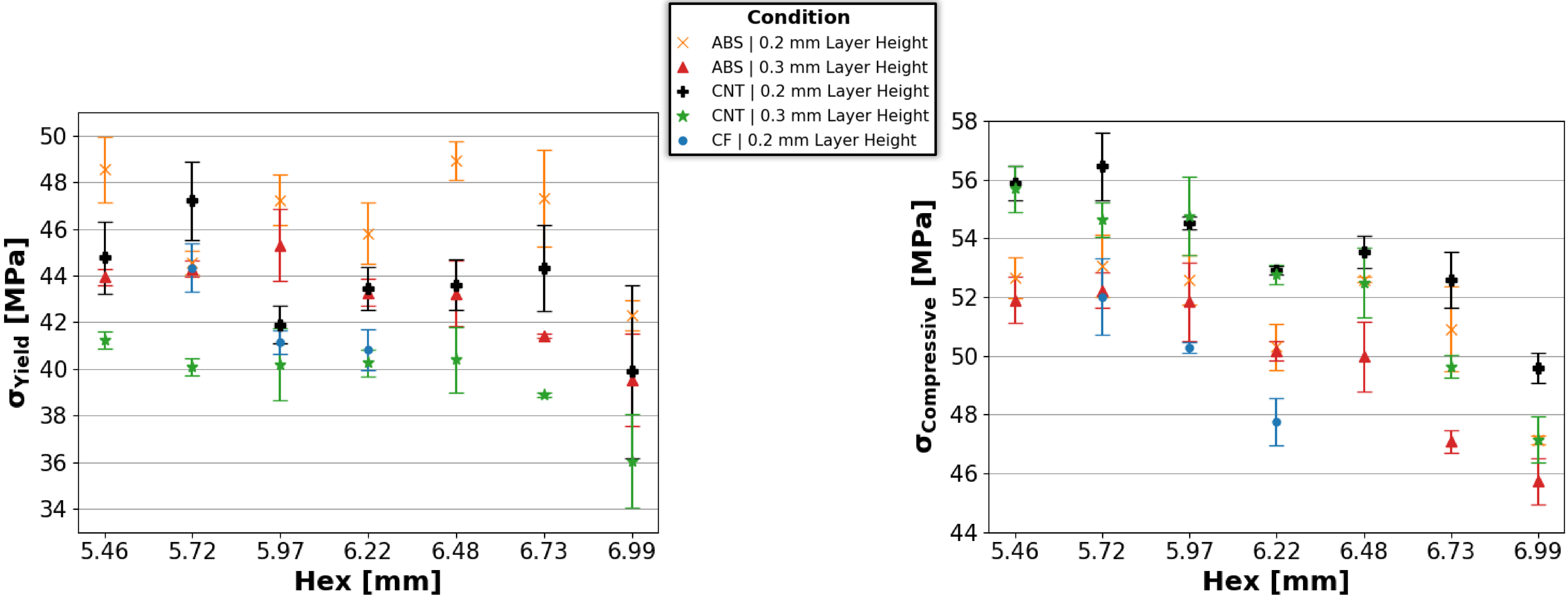
Compression Testing - Results





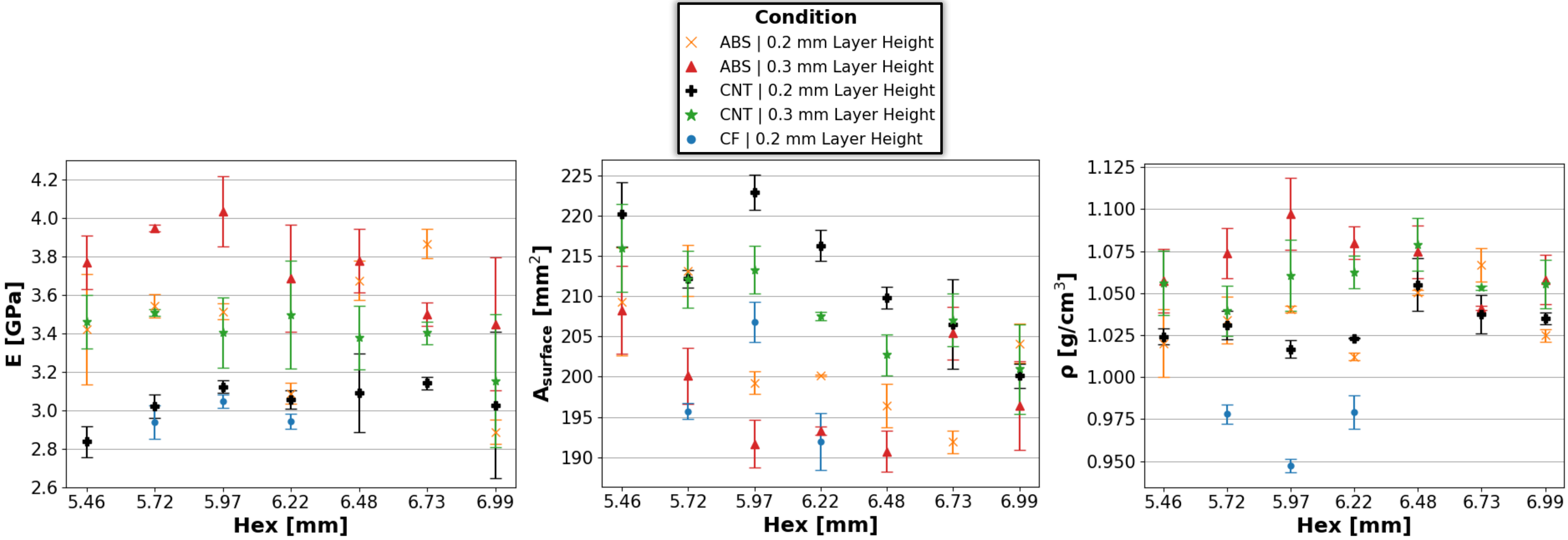
Decreasing compressive strength with increasing hex size
- **0.2 mm and 0.3 mm print layer height**

Compression Testing - Results



Decreasing compressive strength with increasing hex size (0.2mm and 0.3mm print layer height). CNT reinforcement provides higher ultimate compressive strength, but reduced yield.

Compression Testing - Results



Young's Modulus remains relatively constant across hex sizes for all materials.
Decreasing surface area with increasing hex (due to constrained 25.4 mm cross-section).
CF reinforcement results in reduced density (due to increased porosity).

Applying Machine Learning for Classification and Regression

Machine Learning - Classification

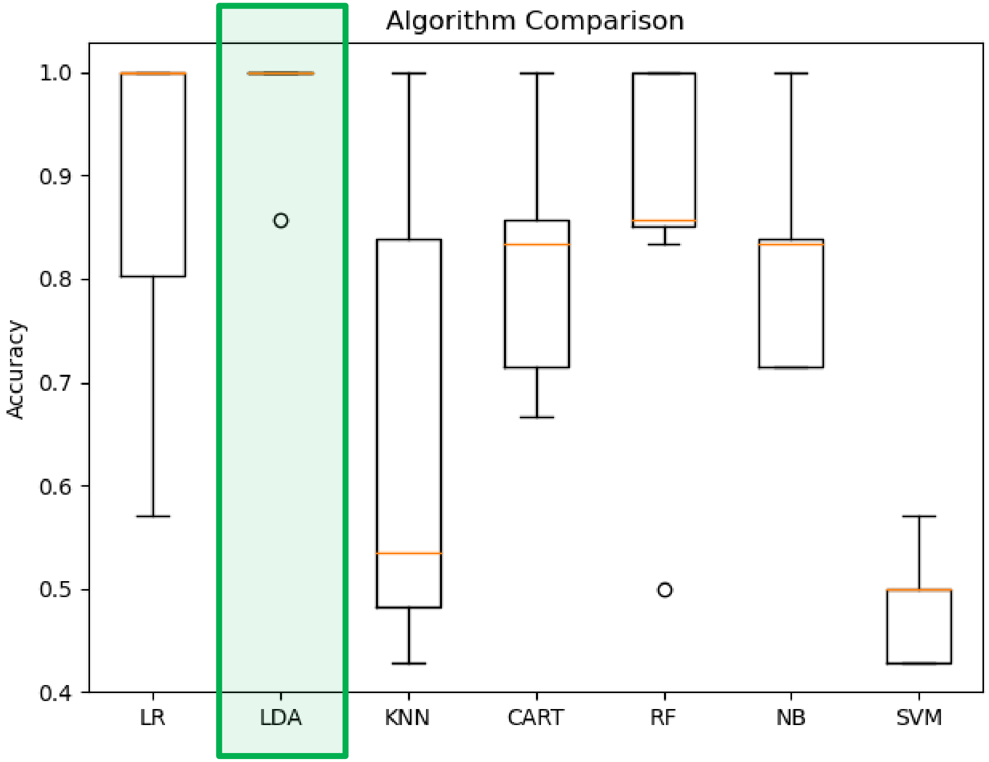
Question: Can we classify material based on features and mechanical properties?

- Hex | Surface Area | Density | Young's Modulus | Compressive Strength

Approach: Leverage standard python libraries and spot-check multiple algorithms for accuracy

- Train/Test Split: 0.8/0.2
- Cross-Validation: stratified 8-fold

Training Results



Algorithm	CV - Accuracy	Std. Deviation
Linear Regression (LR)	0.89	0.16
Linear Discriminant Analysis (LDA)	0.98	0.05
K-Nearest Neighbors (KNN)	0.64	0.21
Decision Tree (CART)	0.81	0.10
Random Forest (RF)	0.84	0.14
Naive Bayes (NB)	0.81	0.09
Support Vector Machine (SVM)	0.48	0.05

Machine Learning - Classification

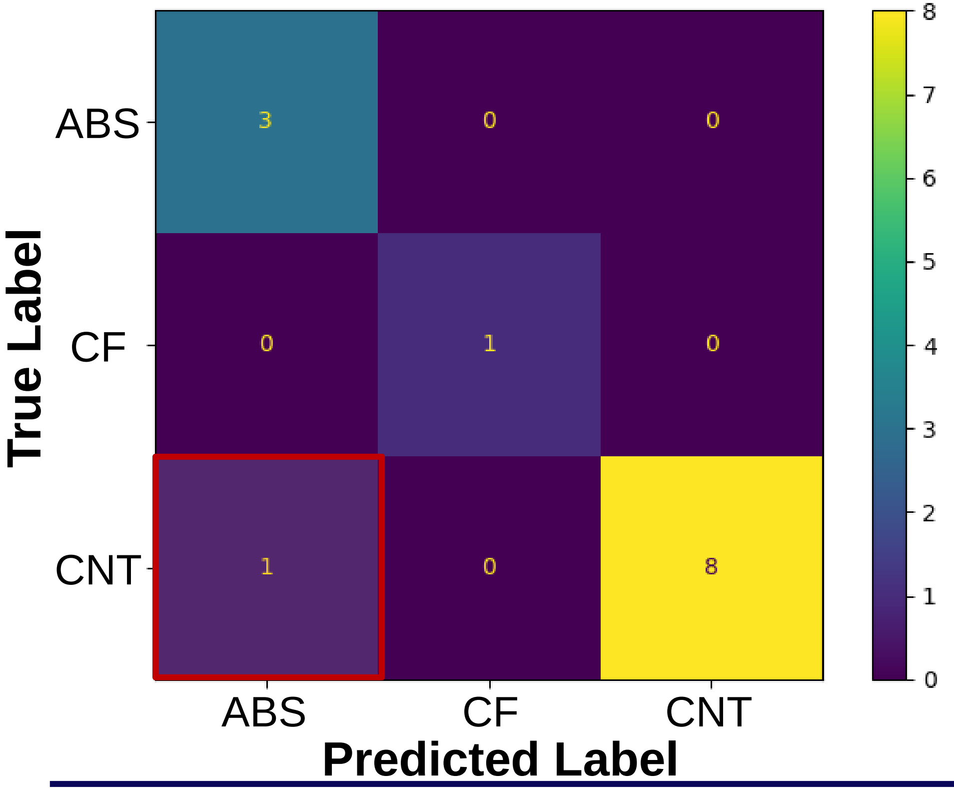
Question: Can we classify material and reinforcement based on features and mechanical properties?

- Hex | Surface Area | Density | Young's Modulus | Compressive Strength

Approach: Leverage standard python libraries and spot-check multiple algorithms for accuracy

- Train/Test Split: 0.8/0.2
- Cross-Validation: stratified 8-fold

Predicted Results



	Precision	Recall	F1-Score
ABS	0.75	1.00	0.86
CF-ABS	1.00	1.00	1.00
CNT-ABS	1.00	0.89	0.94

Test Accuracy = 0.92

LDA performed well at classifying material and reinforcement, even with a small data set.

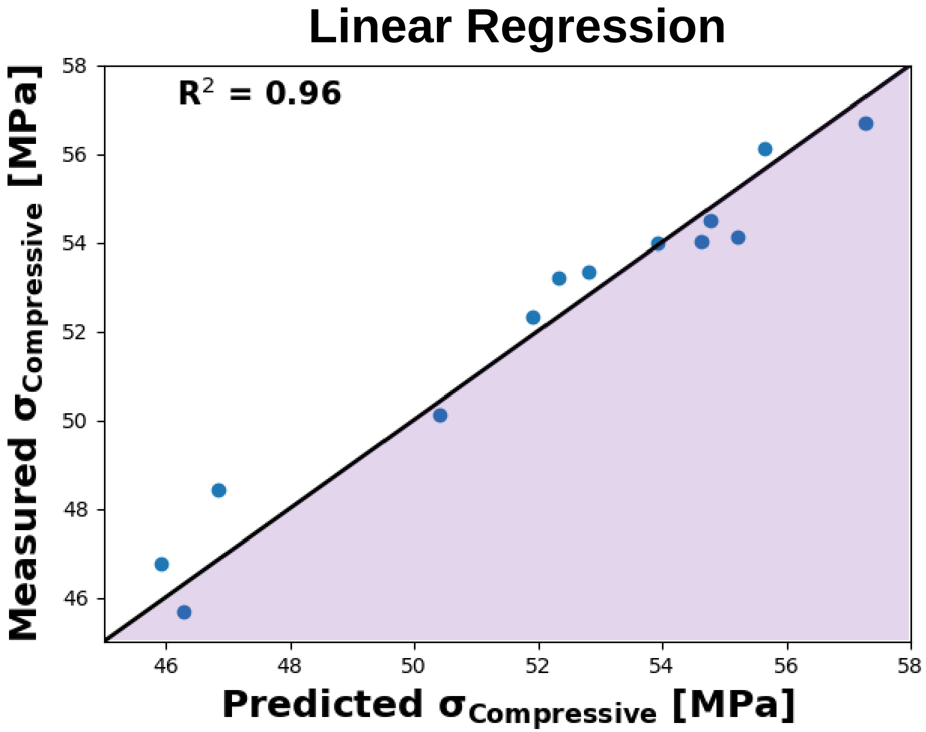
Machine Learning - Regression

Question: Can we predict mechanical properties (compressive strength) based on material features?
- Material | Hex | Build Height | Surface Area | Density | Volume

Approach: Leverage standard python libraries and spot-check multiple algorithms for accuracy
- Train/Test Split: 0.8/0.2

Predicted Results

Algorithm	R^2	Mean Absolute Error
Ridge Regressor	0.91	0.83
Linear Regression	0.96	0.63
K-Neighbors Regressor	0.70	1.70
Gradient Boosting Regressor	0.88	0.99
Random Forest Regressor	0.79	1.40
Extra Trees Regressor	0.82	1.28
Decision Tree Regressor	0.79	1.5
Lasso Regression	0.36	2.34



Predictive models can be used to guide design for targeted performance.

Conclusions

Conducted microscopy and mechanical testing to determine:

- Increasing hex size and print layer height results in increased porosity
- Decreasing compressive strength with increasing hex size (0.2 mm and 0.3 mm print layer height).
- CNT reinforcement provides higher ultimate compressive strength, but reduced yield.
- Increased porosity in upper print layers resulted in consistent failure location.

Implemented machine learning models for classification and regression:

- Material type (ABS, CF-ABS, CNT-ABS) can be classified by LDA with 0.92 accuracy.
- Mechanical property (compressive strength) was predicted by LR with an 0.96 R^2 value.
    - Small dataset could benefit from additional testing.
    - Models can be used to guide and inform design for targeted performance.

Acknowledgements

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